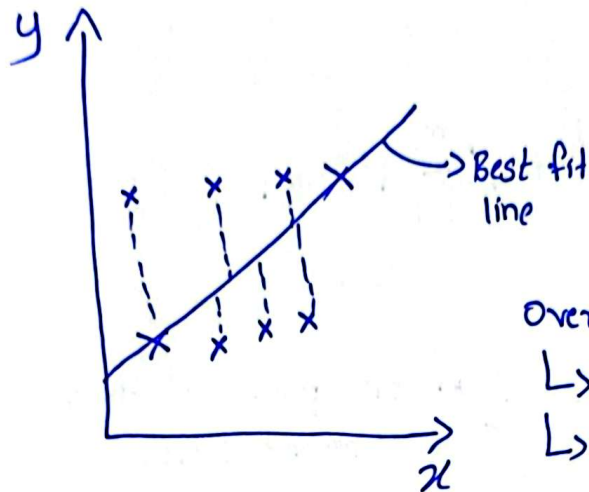


RIDGE REGRESSION (L2 Regularization)



Overfitting

↳ Training Data → High Accuracy → Low Bias

↳ Test Data → Low Accuracy → High Variance

To reduce overfitting, we can use Ridge Regression

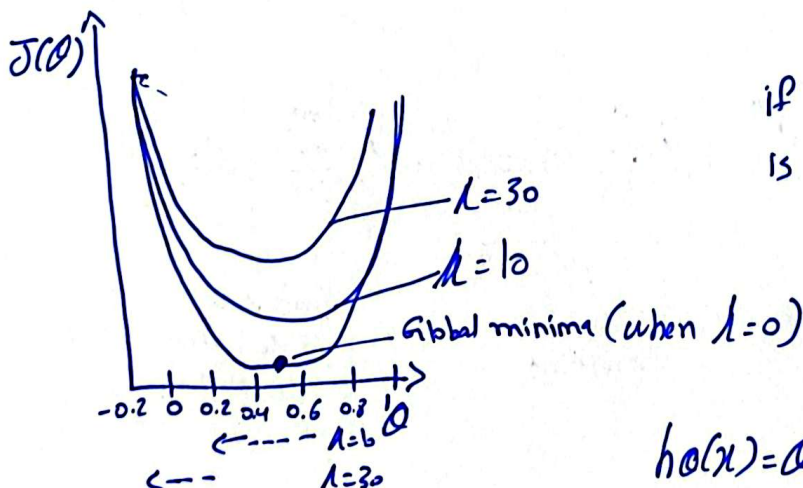
Cost Function

$$\frac{1}{2m} \sum_{i=1}^m (h_{\theta}(x)^i - y^i)^2 + \lambda \sum_{i=1}^m (\text{slope})^2$$

↳ hyperparameter

if $\lambda = 1$

$$\begin{aligned} h_{\theta}(x) &= \theta_0 + \theta_1 x_1 \\ &= 0 + 1 [\theta_1]^2 \\ &> 0 \end{aligned}$$



if λ is increasing, slope is decreasing

$$\begin{aligned} h_{\theta}(x) &= \theta_0 + \theta_1 x_1 + \theta_2 x_2 + \theta_3 x_3 \\ &= \underset{0.34}{0} + 0.52x_1 + 0.48x_2 + 0.24x_3 \end{aligned}$$

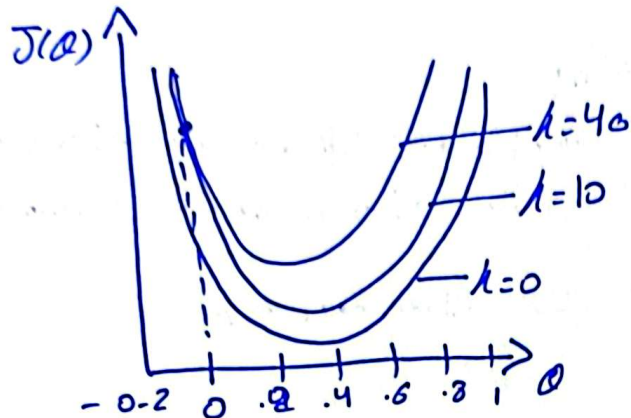
After apply Ridge regression

$$= 0.34 + 0.40x_1 + 0.38x_2 + 0.14x_3$$

LASSO REGRESSION (L1 Regularization) → Feature Selection

Cost Function

$$\frac{1}{2m} \sum_{i=1}^m [h_{\theta}(x)^i - y^i]^2 + \lambda \sum_{i=1}^m |\text{slope}|$$



After one point of time,
 θ will become zero.

$$h_{\theta}(x) = \theta_0 + \theta_1 x_1 + \theta_2 x_2 + \theta_3 x_3 + \theta_4 x_4$$

$$= 0.52 + 0.65x_1 + 0.72x_2 + 0.34x_3 + 0.12x_4$$

Lasso Regression = $0.52 + 0.65x_1 + 0.60x_2 + 0.14x_3$ $\therefore 0.12x_4$ \swarrow removed

Elastic Net (L1 and L2)

Cost Function

$$\frac{1}{2m} \sum_{i=1}^m [h_{\theta}(x)^i - y^i]^2 + \underbrace{\lambda_1 \sum_{i=1}^m (\text{slope})^2}_{\text{reduce overfitting}} + \underbrace{\lambda_2 \sum_{i=1}^m |\text{slope}|}_{\text{feature selection}}$$